



# Comparison of Acoustic Models and Trajectory Generation Methods for an Acoustically-Aware Aircraft

Kasey A. Ackerman and Irene M. Gregory

NASA Langley Research Center

Hampton, VA 23681

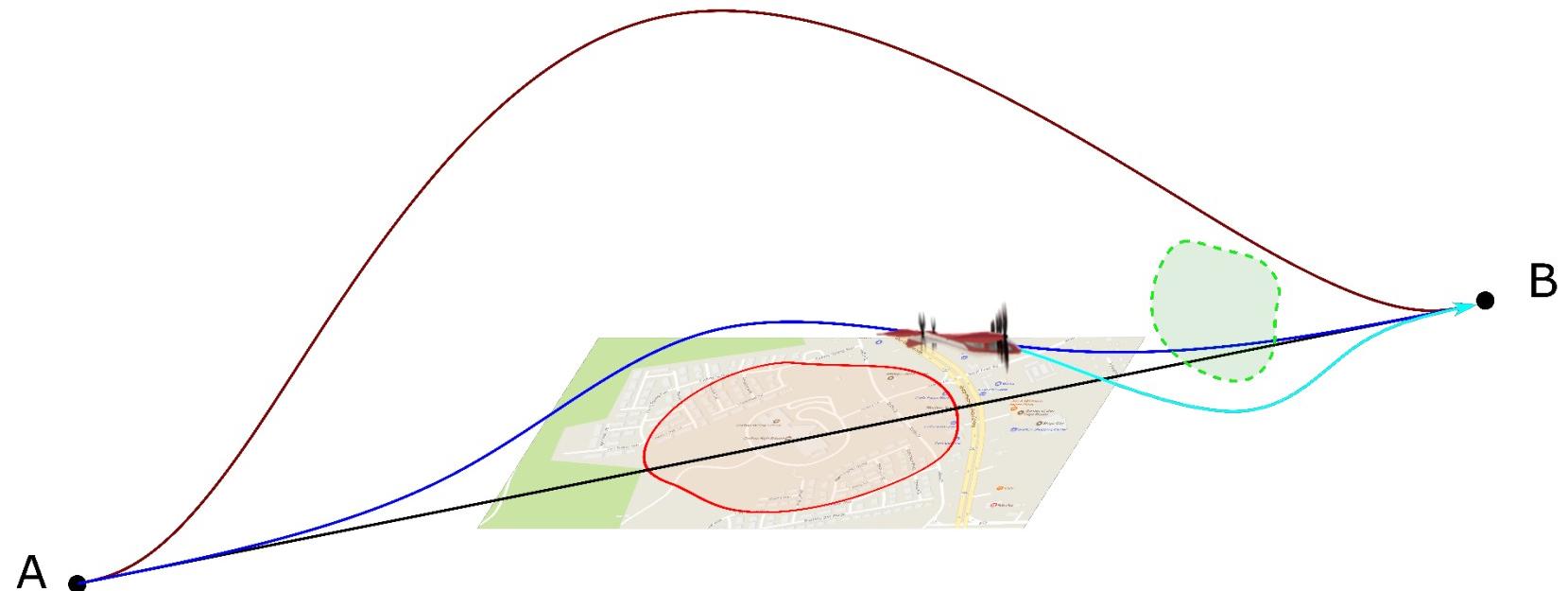
AIAA SciTech Forum

National Harbor, MD

January 2023

# Motivation

- Noise management is one of the major barriers to Urban Air Mobility
- Approaches to noise mitigation (non-exhaustive)
  - Vehicle configuration
  - Directivity control via propeller phase synchronization
  - *Trajectory optimization*



# Objective



- Create framework for trajectory generation integrating location-based acoustic metrics and vehicle performance limitations
  - Multiple trajectory optimization methods and acoustic noise models
  - Mission-relevant constraints
    - Mission duration, airspace restrictions, ...
  - Vehicle dynamic constraints
    - Aircraft structural limitations, min/max airspeed, ...
  - Vehicle separation/obstacle avoidance
  - Acoustic constraints at a number of discrete observer locations



# Comparison of Models and Methods

- Two acoustic source noise models
  - Omni-directional model based on propeller tip Mach Number
  - Directional hemisphere-based model
- Two trajectory planning methods
  - Pre-mission full-trajectory planner using polynomial parameterization
  - Receding horizon (near) real-time nonlinear model predictive control (MPC) trajectory planner
- Compare trajectory planning performance using both noise models and trajectory generation methods

# Vehicle Dynamics



- Fixed-wing distributed propulsion aircraft
  - Can represent tilt-wing or split-propulsion vehicle in forward flight
  - Coordinated flight aircraft model\*
    - Basic aerodynamic model
    - Simplified motor/propeller model
    - Assumes underlying tracking controller
- Parameter values taken from model of NASA's GL-10 aircraft



Figure credit: NASA

\*Adapted from J Hauser, R Hindman, "Aggressive Flight Maneuvers," IEEE Conference on Decision and Control, 1997.

# Omni-Directional Acoustic Model

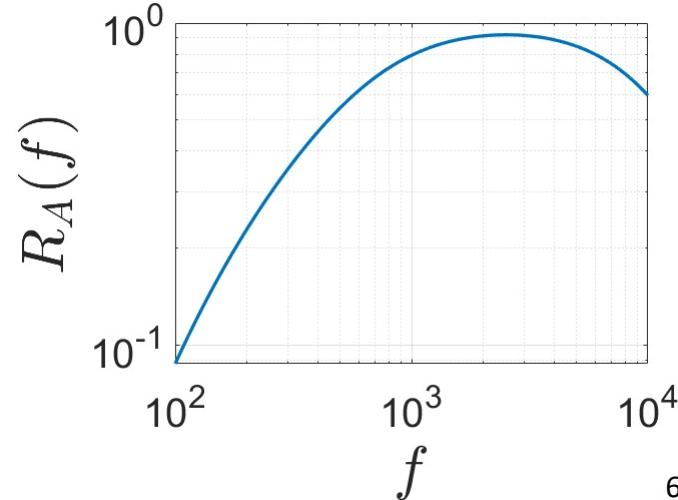
- Metric is *sound pressure level (SPL)*
- Model data fit from the Propeller Analysis System of the Aircraft Noise Prediction Program (PAS-ANOPP)
- Based on effective propeller tip Mach number
- Optional frequency weighting

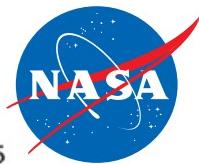
$$SPL = 10 \log_{10} \left( \frac{1}{\hat{p}^2} \sum_{k=0}^{N_f} \left[ \hat{p}_{\text{rms},k}^2 \left( \frac{M_{\text{eff}}}{\hat{M}_{\text{eff}}} \right)^{\xi_k} R_A(f_k) \right] \left( \frac{\hat{r}}{r} \right)^2 N_p \right)$$

Frequency weighting
Number of propellers  
Propeller speed
Distance to observer

$$M_{\text{eff}} = \frac{M_t}{1 + J(1 - M_t)}$$

$$M_t = \omega_p d_p / 2c$$



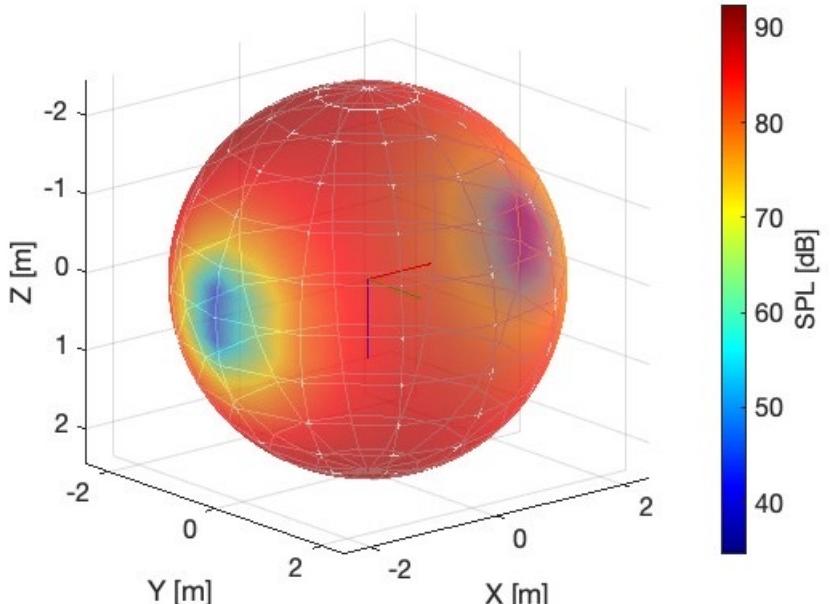
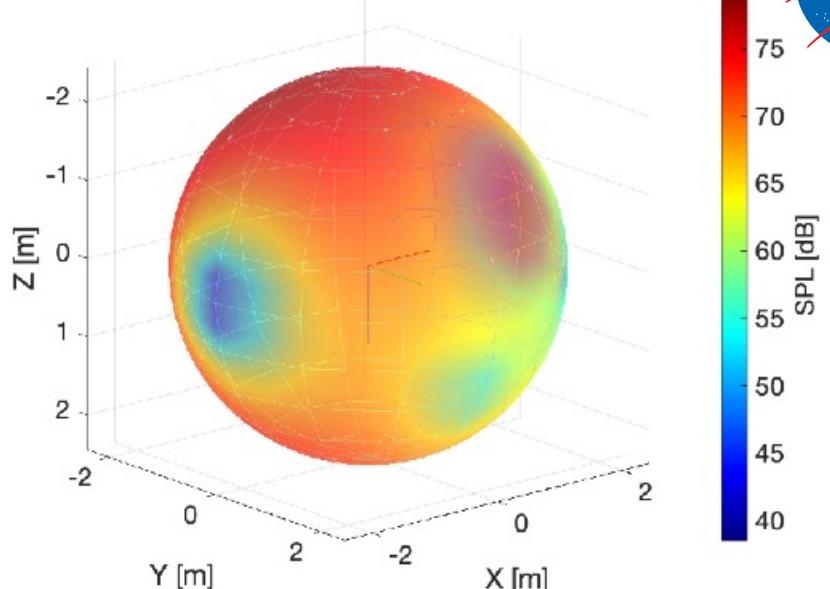


# Hemisphere Acoustic Model

- Metric is *sound pressure level (SPL)*
- Model data from the Propeller Analysis System of the Aircraft Noise Prediction Program (PAS-ANOPP)
- Directional noise emission
- Interpolation over airspeed, angle of attack, propeller speed, direction to observer

$$SPL_{obs} = SPL + 20 \log_{10} \left( \frac{\hat{r}}{r} \right) + 6 + R_A(f) + 10 \log_{10}(N_p)$$

Pressure doubling      Frequency weighting  
Distance to observer      Number of propellers



# Pre-Mission Trajectory Planner\*



- Full trajectory optimization with polynomial parameterization
  - Simplified (differentially flat) vehicle dynamics, acoustic source model, and propagation model
  - Implemented as a 2<sup>nd</sup> order Hermite interpolation problem
  - Bézier polynomial representation of spatial path and parametric speed
  - Numeric (discrete) evaluation of mid- to high-fidelity acoustic source and propagation models

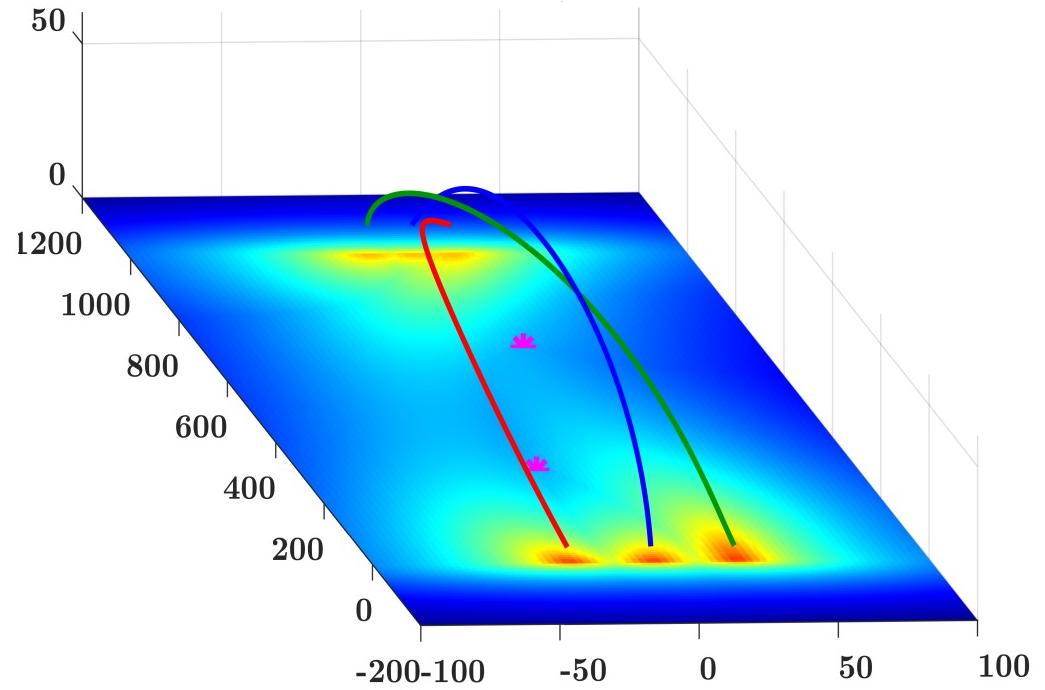


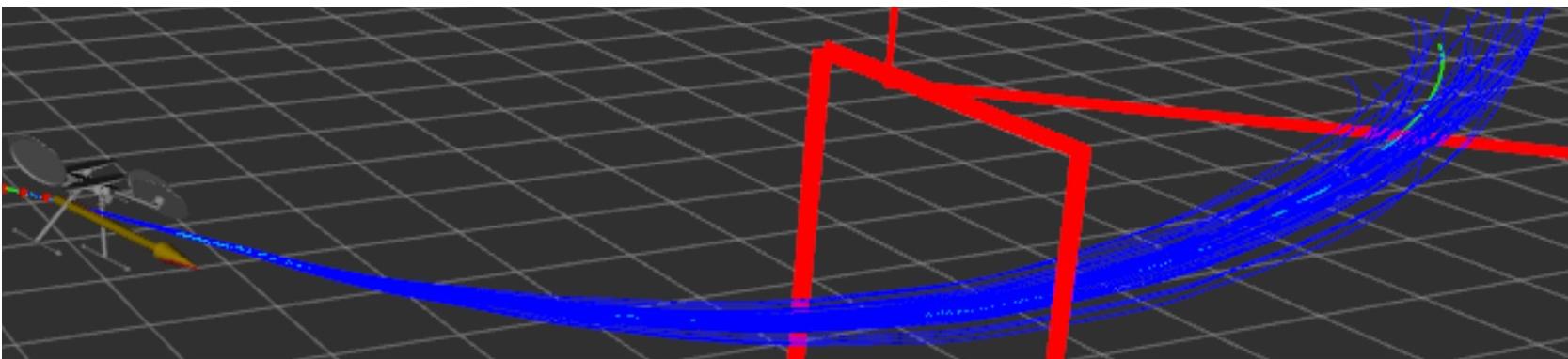
Figure Credit: \*KA Ackerman and IM Gregory, "Trajectory Generation for Noise-Constrained Autonomous Flight Operations," AIAA SciTech Forum, Jan 2020. AIAA-2020-0978



# MPC Motion planner\*

## ■ Model Predictive Path Integral Control (MPPI)\*\*

- Stochastic optimization technique used as nonlinear MPC
- Framework to efficiently solve a finite horizon nonlinear optimal control problems
- State cost function can be arbitrarily complex
- Sampling-based optimization leverages GPU for efficient computation

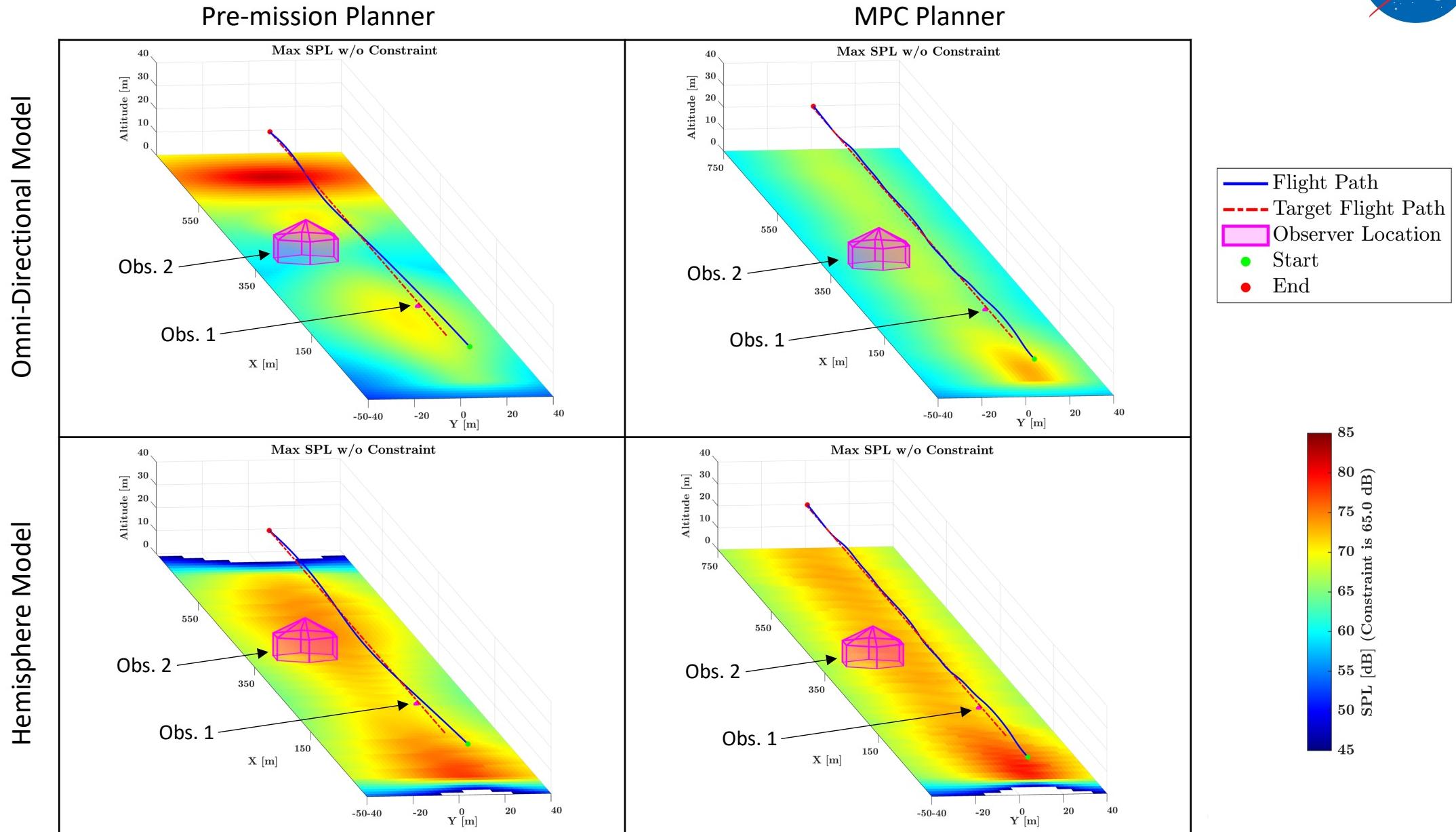


**Figure credit:** J Pravitra, KA Ackerman, N Hovakimyan, EA Theodorou, "L1-Adaptive MPPI Architecture for Robust and Agile Control of Multirotors," IROS, 2020.

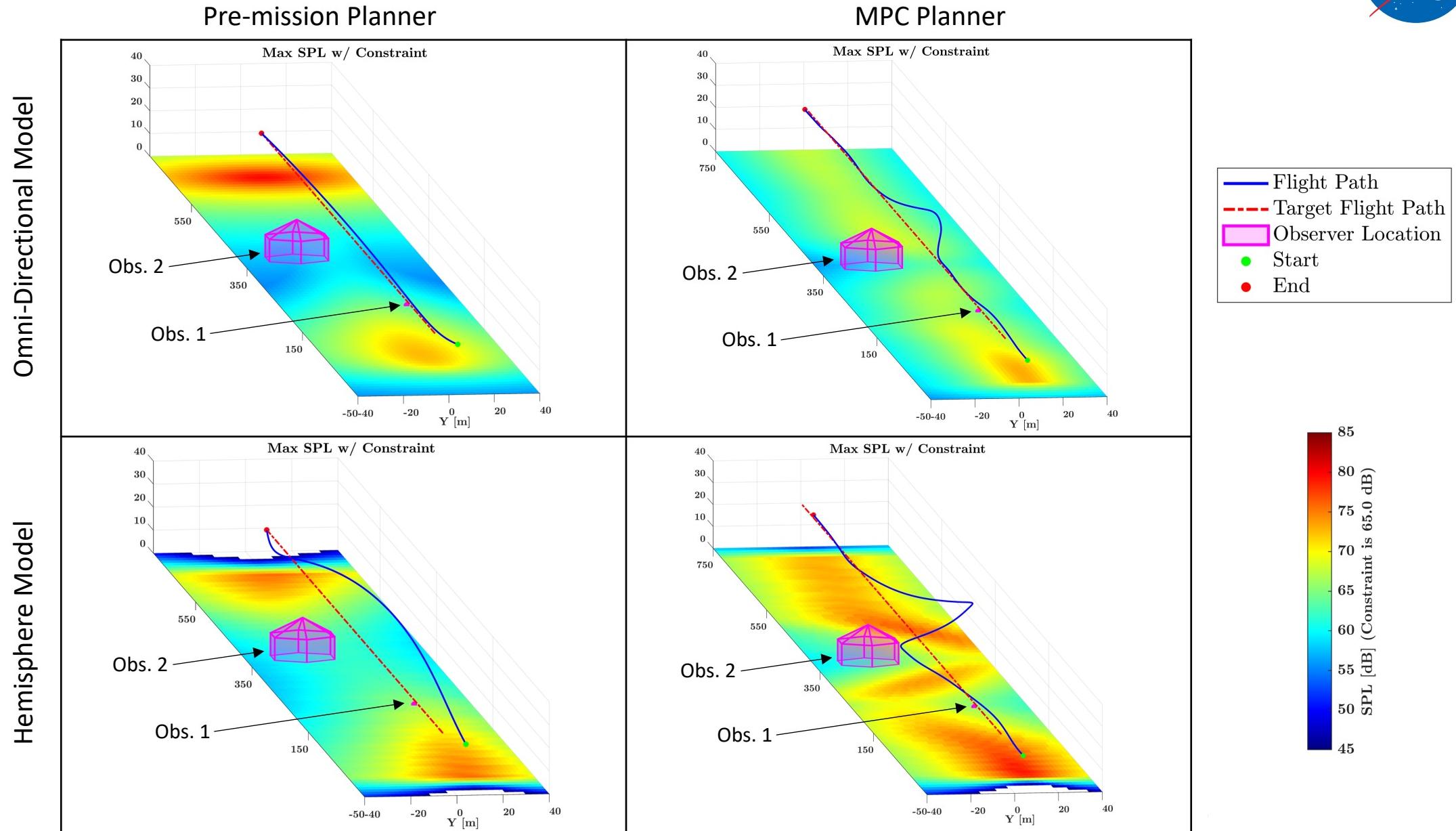
\*KA Ackerman, IM Gregory, N Hovakimyan, EA Theodorou, "A Model Predictive Control Approach for In-Flight Acoustic Constraint Compliance," AIAA SciTech Forum, 2021. AIAA-2021-1958

\*\*G Williams, P Drews, B Goldfain, JM Rehg, EA Theodorou, "Information Theoretic Model Predictive Control: Theory and Applications to Autonomous Driving," IEEE Transactions on Robotics, 2018.

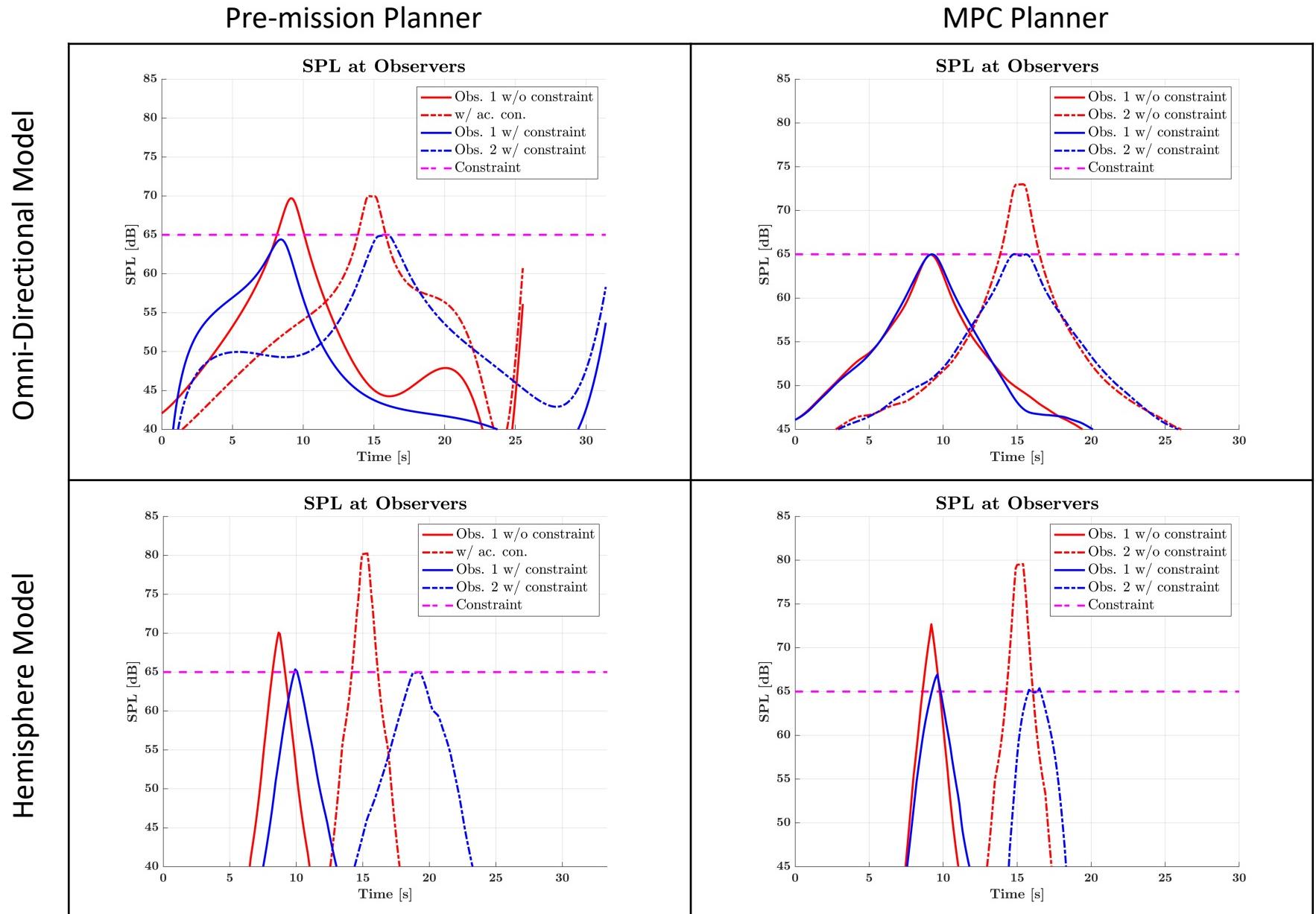
# Comparison – Acoustic Constraint Inactive



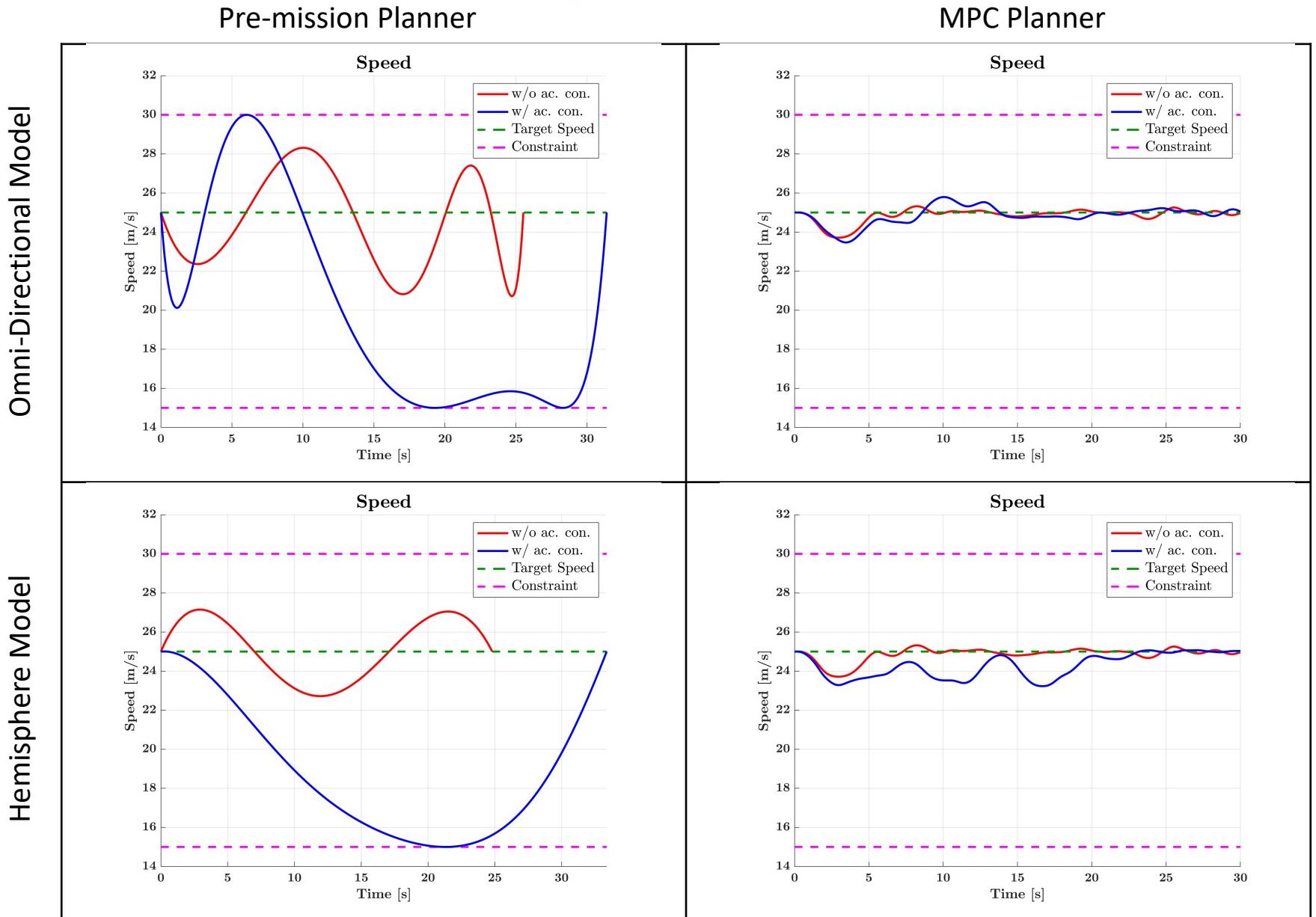
# Comparison – Acoustic Constraint Active



# Comparison – Sound Pressure Level



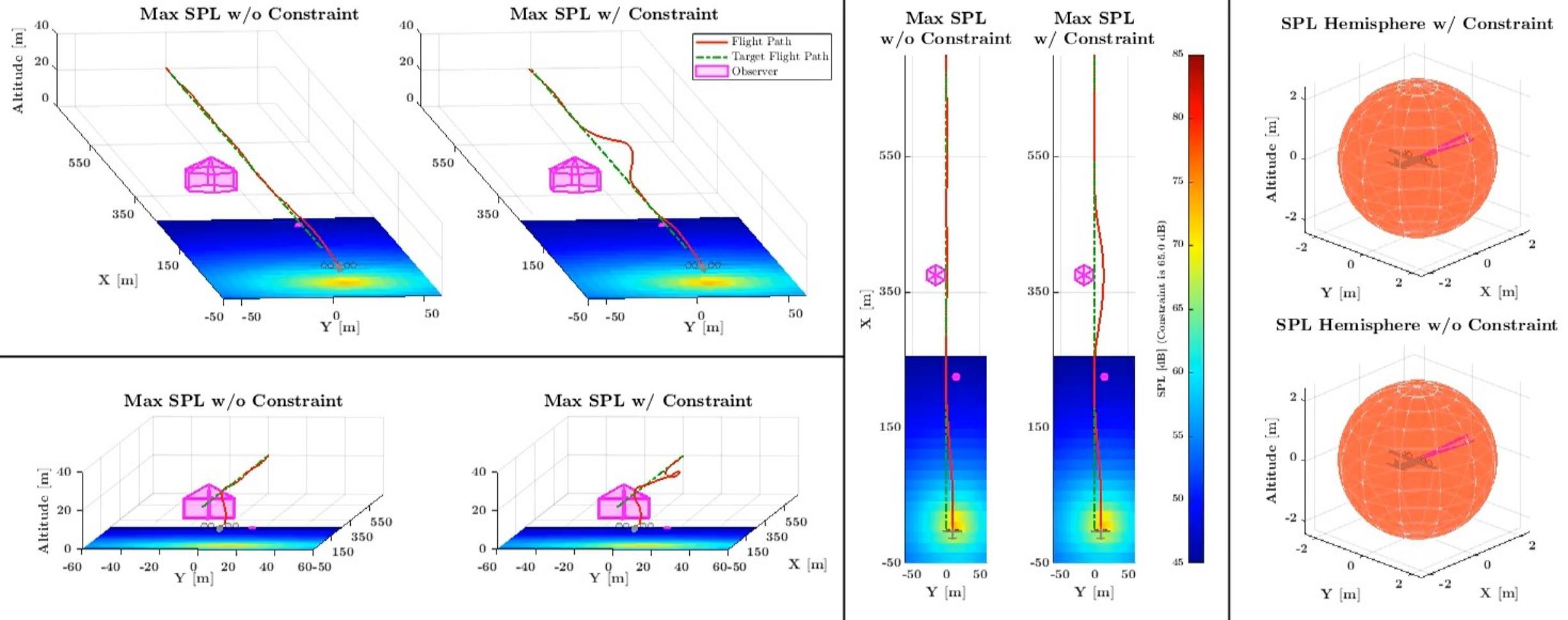
# Comparison – Vehicle Speed



# Noise Model Comparison



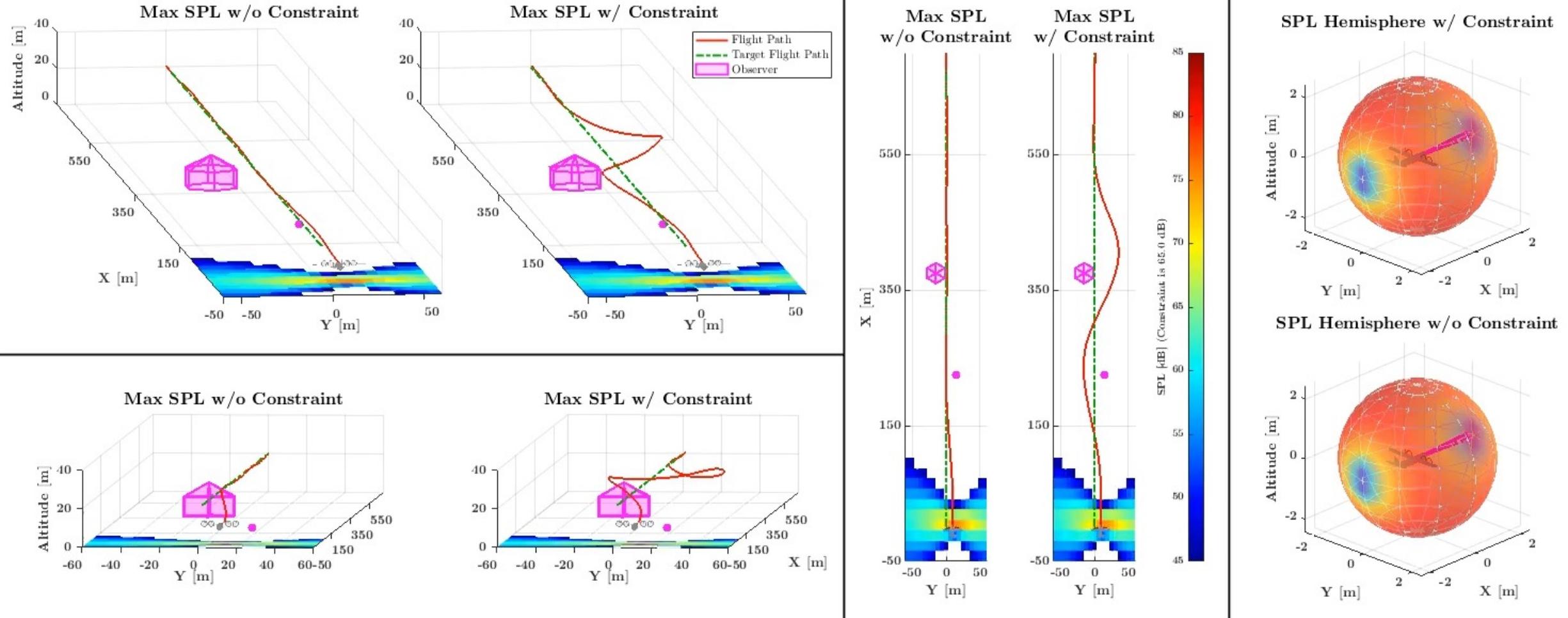
## ■ Omni-directional propeller speed model



# Noise Model Comparison



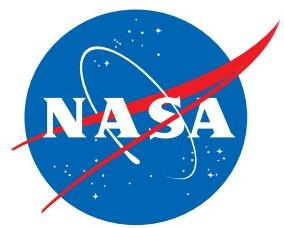
## Hemisphere model



# Summary

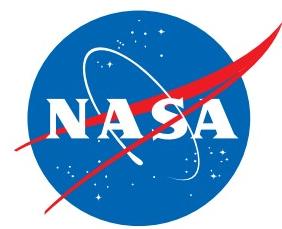


- Compared two different trajectory planning methods and two acoustic noise models
  - Full trajectory planning with guaranteed constraint satisfaction
  - Finite horizon planning has greater freedom in trajectory planning
    - Better able to exploit directionality of hemisphere model
  - Directionality of noise emission makes difference in maximum noise levels seen on ground
    - Higher peak noise, but shorter duration with hemisphere model
- Future efforts focused on combining planner methods to leverage advantages of each
- Acknowledgements
  - NASA's Revolutionary Vertical Lift Technology Project
  - Dr. Kyle Pascioni (NASA Langley Research Center)
  - Dr. Javier Puig Navarro (National Institute of Aerospace)



POC: Kasey Ackerman  
[kasey.ackerman@nasa.gov](mailto:kasey.ackerman@nasa.gov)

# Background Material



# Vehicle Dynamics



- Fixed-wing distributed propulsion aircraft
  - Can represent tilt-wing or split-propulsion vehicle in forward flight
  - Coordinated flight aircraft model\*
    - Includes basic aerodynamic model
    - Assumes underlying tracking controller
  - Dynamics:

$$\dot{\boldsymbol{x}} = \boldsymbol{v}$$
$$\dot{\boldsymbol{v}} = \boldsymbol{g} + \boldsymbol{R}\boldsymbol{a}_v$$
$$\dot{\boldsymbol{q}} = \frac{1}{2}\boldsymbol{q} \otimes \begin{bmatrix} 0 \\ \boldsymbol{\omega}_v \end{bmatrix}$$
$$\boldsymbol{\omega}_v = [p_s \quad -\boldsymbol{e}_3 (\boldsymbol{a}_v + \boldsymbol{g}) / V \quad \boldsymbol{e}_3 \boldsymbol{g} / V]^T$$
$$[T \quad \alpha \quad p_s]^T = \boldsymbol{u}$$
$$\boldsymbol{e}_3 = [0 \quad 0 \quad 1]^T$$

Coordinated flight constraint

\*Adapted from J Hauser, R Hindman, "Aggressive Flight Maneuvers," IEEE Conference on Decision and Control, 1997.

# Vehicle Dynamics



## ■ Aerodynamic model:

$$\mathbf{a}_v = \begin{bmatrix} \frac{T}{m} \cos \alpha - \frac{\rho V^2 S}{2m} (\sin \alpha (C_{N_0} + C_{N_\alpha} \alpha) + \cos \alpha (C_{A_0} + C_{A_{\alpha^2}} \alpha^2)) \\ 0 \\ -\frac{T}{m} \sin \alpha - \frac{\rho V^2 S}{2m} (\cos \alpha (C_{N_0} + C_{N_\alpha} \alpha) - \sin \alpha (C_{A_0} + C_{A_{\alpha^2}} \alpha^2)) \end{bmatrix}$$

Highlighted variables:  
Thrust – blue  
AoA – red  
Aero Coeff - green

## ■ Propeller/motor model:

$$T = c_2(J)\omega_p^2 + c_1(J)\omega_p + c_0(J)$$

$$J = \frac{2\pi V \cos \alpha}{\omega_p d_p}$$

Advance ratio

## ■ Parameter values taken from model of NASA's GL-10 aircraft



# Pre-Mission Trajectory Planner



- Full trajectory optimization with polynomial parameterization
  - Simplified vehicle dynamics, acoustic source model, and propagation model
  - Implemented as a 2<sup>nd</sup> order Hermite interpolation problem
  - Bézier polynomial representation of spatial path and parametric speed
    - Computationally efficient algorithms
    - No discretization of trajectory or constraint functions
    - Constraints can be satisfied to arbitrary precision
  - Assumes differential flatness of dynamics and constraints
  - Numeric (discrete) evaluation of mid- to high-fidelity acoustic source and propagation models

\*KA Ackerman and IM Gregory, “Trajectory Generation for Noise-Constrained Autonomous Flight Operations,” AIAA SciTech Forum, Jan 2020. AIAA-2020-0978

# Pre-Mission Trajectory Planner



## ■ Differentially flat dynamics

$$\begin{aligned}\dot{x}(t) &= V(t) \begin{bmatrix} \cos(\gamma(t)) \cos(\chi(t)) \\ \cos(\gamma(t)) \sin(\chi(t)) \\ -\sin(\gamma(t)) \end{bmatrix} \\ m\dot{V}(t) &= T(t) - D(t)\end{aligned}$$

## ■ Spatial path and timing law

- Derive all other variables from path and timing law

$$x(\zeta) = \sum_{k=0}^5 \bar{x}_k b_k^n(\zeta), \quad \zeta \in [0, 1]$$

$$\theta = \frac{d\zeta(\hat{t})}{d\hat{t}} = \sum_{k=0}^{n_\theta} \bar{\theta}_k b_n^k(\hat{t}), \quad \hat{t} = \frac{t}{t_f}$$

$$\zeta(\hat{t}) = \int_0^{\hat{t}} \theta(\tau) d\tau$$

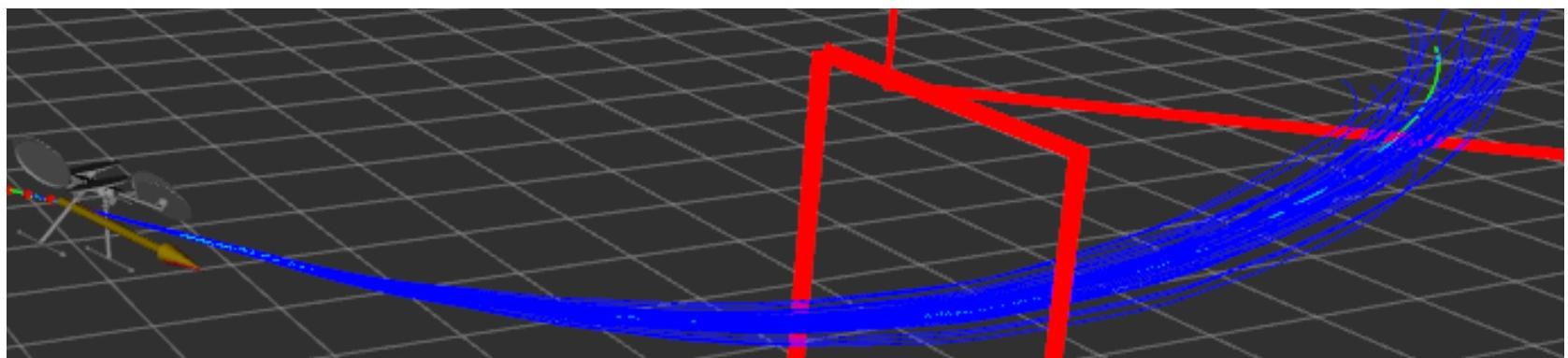
\*KA Ackerman and IM Gregory, "Trajectory Generation for Noise-Constrained Autonomous Flight Operations," AIAA SciTech Forum, Jan 2020. AIAA-2020-0978

# MPC Motion Planner\*



## ■ Model Predictive Path Integral Control (MPPI)\*\*

- Sample thousands of control sequences,  $\nu_t \sim \mathcal{N}(u_t, \Sigma)$ , propagate trajectories in parallel
- Exponential cost-weighted averaging to update mean of optimal control distribution,  $u_t$
- Propagate mean optimal control sequence to obtain nominal trajectory



**Figure credit:** J Pravitra, KA Ackerman, N Hovakimyan, EA Theodorou, “L1-Adaptive MPPI Architecture for Robust and Agile Control of Multirotors,” IROS, 2020.

\*KA Ackerman, IM Gregory, N Hovakimyan, EA Theodorou, “A Model Predictive Control Approach for In-Flight Acoustic Constraint Compliance,” AIAA SciTech Forum, 2021. AIAA-2021-1958

# MPC Motion Planner



## ■ Implementation\*

- Discrete-time dynamics  $\mathbf{z}_{t+1} = \mathbf{f}(\mathbf{z}_t, \boldsymbol{\nu}_t)$ ,  $\boldsymbol{\nu}_t \sim \mathcal{N}(\mathbf{u}_t, \Sigma)$
- Cost functional

$$J(\mathbf{U}) = \mathbb{E} \left[ \phi(\mathbf{z}_{t+T}) + \sum_{k=t}^{t+T-1} q(\mathbf{z}_k) + \lambda \mathbf{u}_k^\top \Sigma^{-1} (\boldsymbol{\nu}_k - \mathbf{u}_k) \right]$$

- State cost and control weight for each control sequence

$$\begin{aligned} S(\mathbf{V}_t^i) &= \phi(\mathbf{z}_{t+T}^i) + \sum_{k=t}^{t+T-1} q(\mathbf{z}_k) \\ w(\mathbf{V}_t^i) &= \exp \left[ -\frac{1}{\lambda} \left( S(\mathbf{V}_t^i) - \sum_{k=t}^{t+T-1} \mathbf{u}_t' T \Sigma^{-1} \boldsymbol{\nu}_k^i - \beta \right) \right] \end{aligned}$$

- Approximate optimal control

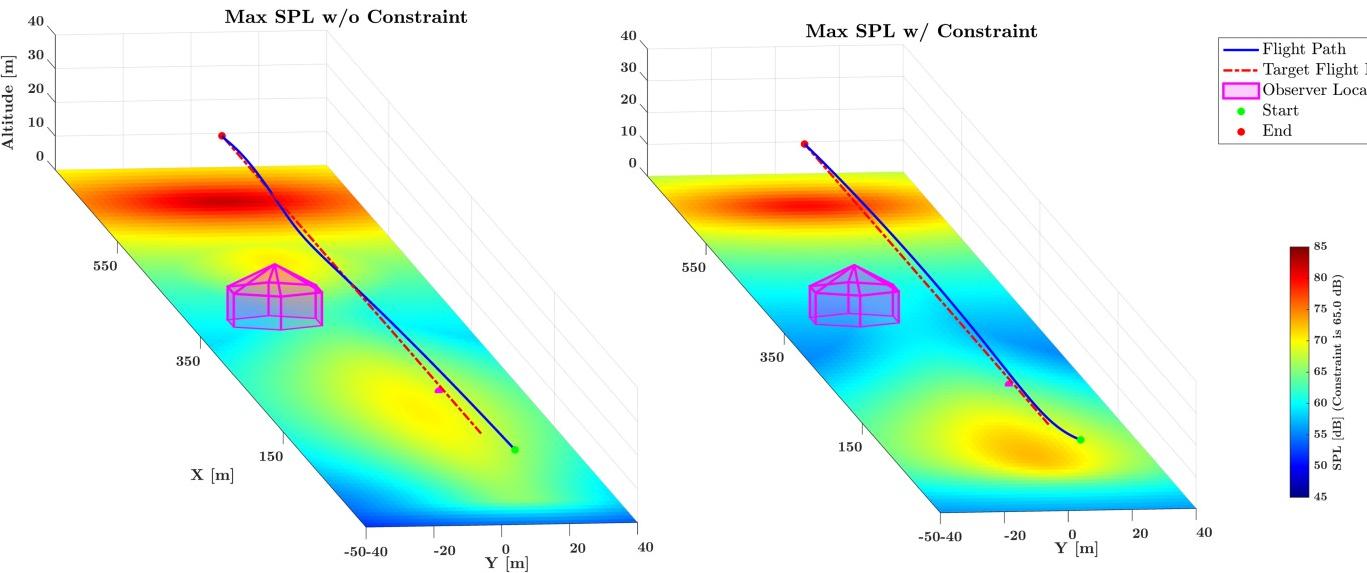
$$\mathbf{u}_t^* \approx \mathbf{u}_t = \mathbf{u}'_t + \frac{1}{\sum_{i=1}^{N_s} w(\mathbf{V}_t^i)} \sum_{i=1}^{N_s} w(\mathbf{V}_t^i) (\boldsymbol{\nu}_t^i - \mathbf{u}_t^i),$$

\*KA Ackerman, IM Gregory, N Hovakimyan, EA Theodorou, "A Model Predictive Control Approach for In-Flight Acoustic Constraint Compliance," AIAA SciTech Forum, 2021. AIAA-2021-1958

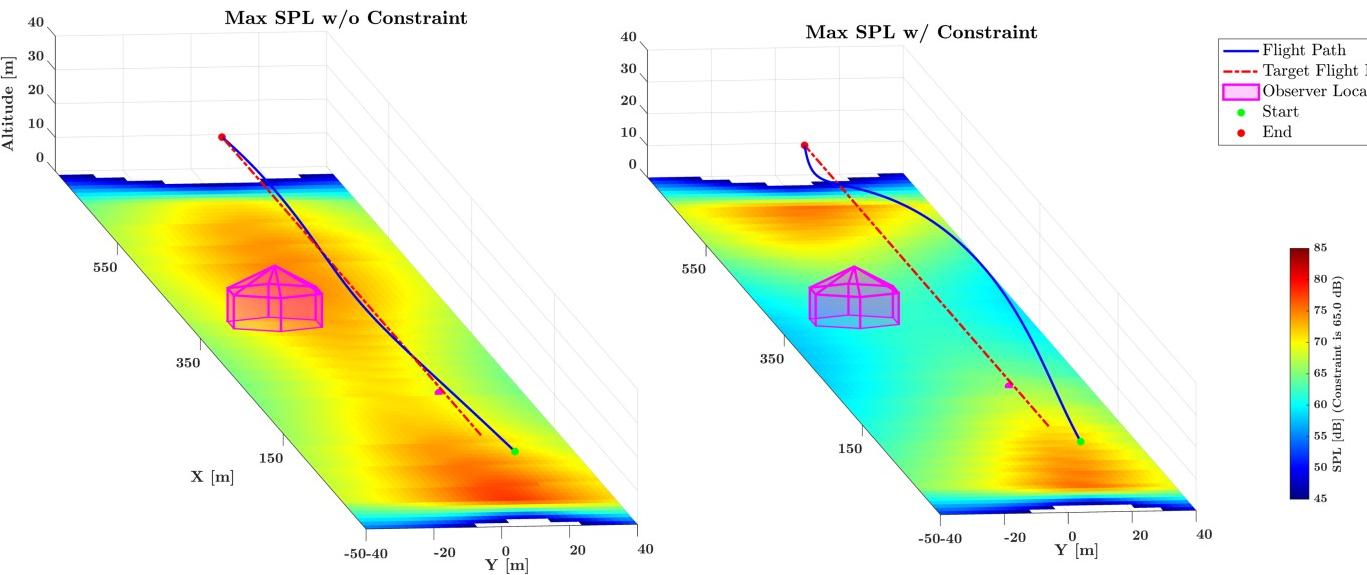
# Noise Model Comparison – Pre-mission Planner



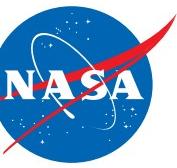
Omni-Directional Model



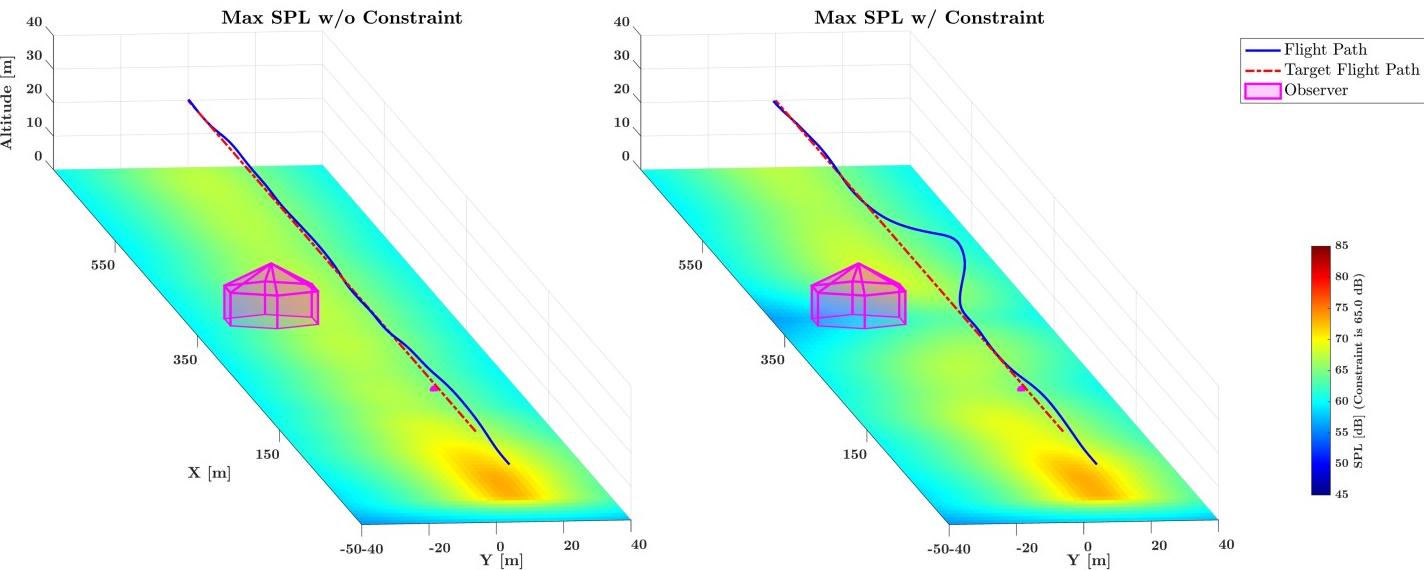
Hemisphere Model



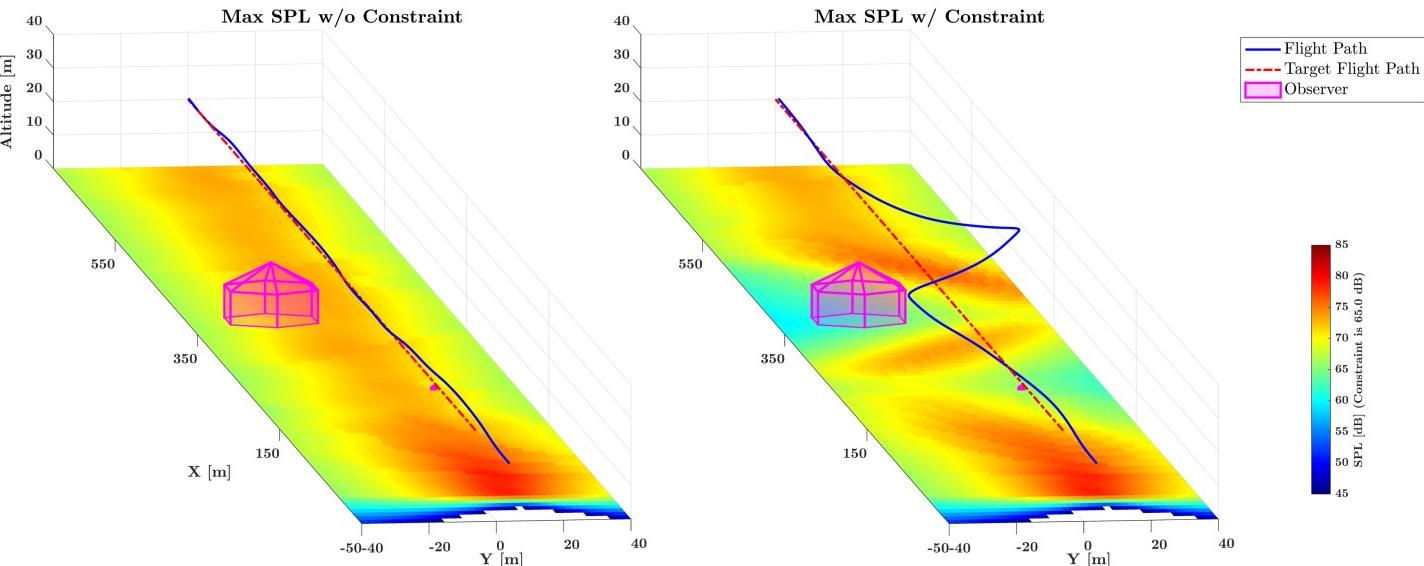
# Noise Model Comparison – MPC Planner



Omni-Directional Model



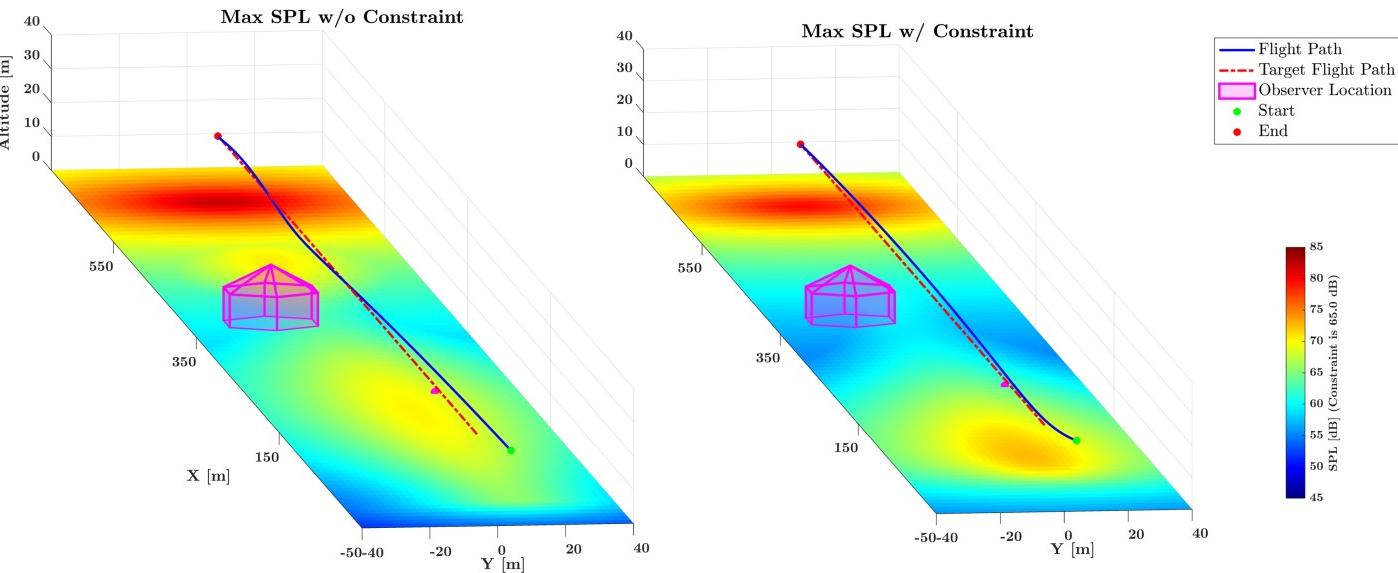
Hemisphere Model



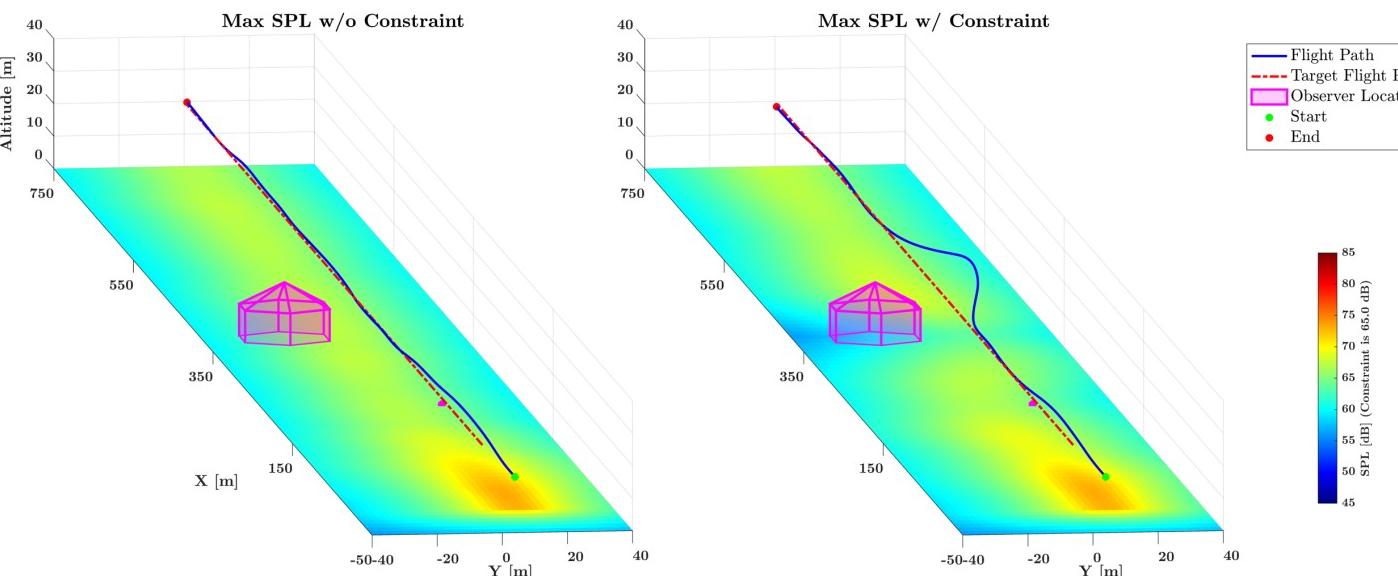
# Planner Comparison – Omni-directional model



Pre-mission Planner



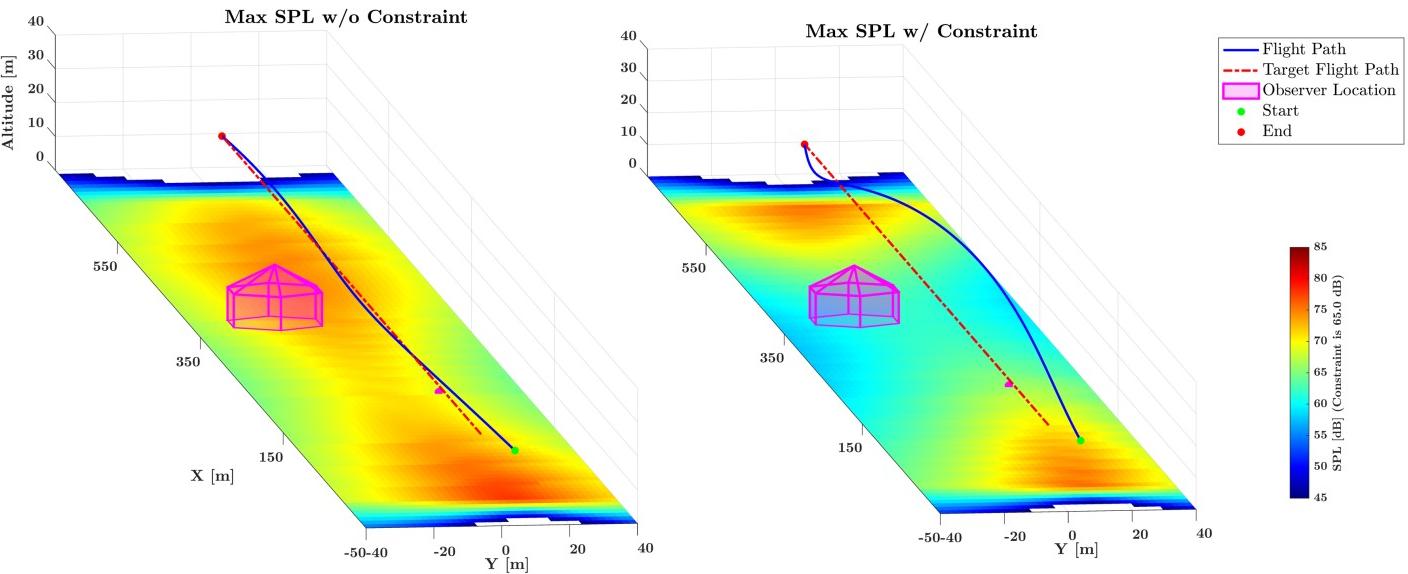
MPC Planner



# Planner Comparison – Hemisphere Model



Pre-Mission Planner



MPC Planner

